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CEREBRAL WEEVIL: A MACHINE LEARNING MODEL FOR HEMISPHERIC CATEGORIZATION OF COMPLEX VISUAL PATTERNS

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The voluntary informed consent of the subjects used in this research was obtained as required by Air Force Regulation 169-3.

This technical report has been reviewed and is approved for publication.

FOR THE COMMANDER

CHARLES BATES, JR.
Director, Human Engineering Division
Armstrong Aerospace Medical Research Laboratory

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This report establishes the role of machine learning as a new human performance modeling technique. Learning mechanisms are modeled based on an empirical analysis of psychological reality and are subsequently tested empirically for their demonstration of that reality. Any variations in differences are considered in terms of changes to both future experimental studies of humans, and new evolvements in the programs used to model the reality. The reality used for this study involved hemispheric processing in learning visual patterns. The factors which influence hemispheric processing are modelled using the ID3 inductive machine learning technique. Various subsets of training data were used to assess the point of convergence between the research data and the model. The model successfully simulates the experimental data when it approaches a subset containing 90% of the examples. Conclusions look at ways to improve the model's convergence at a much lower percentage of examples induced.

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Preface

The research underlying this report was performed by the Harry G. Armstrong Aerospace Medical Research Laboratory, Human Engineering Division, Wright-Patterson AFB, Ohio in support of Work Unit 71841046, Strategic Information and Force Management. The hemispheric process research which formed the basis for the model was enabled through the expert support of Dr. Ron Katsuyama, University of Dayton Psychology Dept., while he was in residence as a National Research Council Associate at the Armstrong Aerospace Medical Research Laboratory, Human Engineering Division. The machine learning research, discussion, and implementation was accomplished with the assistance of Dr. Douglas Fisher, Vanderbilt University Dept. of Computer Science.

Also, the author gratefully acknowledges the support of other key support personnel. The support of the following Systems Research Laboratory personnel was essential in conducting hemispheric research. Bill McGovern who served as experimenter; Curt Mayrand and Brian Porter for their adept programming skills and advice; and Greg Bothe who provided timely insights and oversaw the engineering/hardware development.

I would also like to thank Mr. Walt Summers, Lt. Col. William Marshak, and Mr. Don Monk, AAMRL/HE, for their support of this research.

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INTRODUCTION

There has been much work recently to compose computer models of the cognitive processes that govern the thinking and perception of humans (see Anderson 1983; Marr 1982; Newell, 1980; Pinker, 1985). Many of these models are based on empirical relationships derived from analysis of data taken from human subjects in experimental tasks. Such tasks are employed to gain understanding of human cognitive events. To the extent that these events may be simulated via artificial intelligence techniques -in particular machine learning- one can conclude that the reality of cognition is indeed operable. Although computer models have usually been proposed for problem solving and perception, there has been a dearth of application to the areas of attention and processing between the two cerebral hemispheres of the brain. Hence, the intent of this report is to propose a machine learning model that categorizes patterns in accordance with properties of attention and cerebral laterality. The domain of face recognition will be used to demonstrate human and machine learning. The content of this model will be a summarization of results collected from subjects in a series of match-to-sample recognition tasks (see Katsuyama, McNeese, & Schertler, 1987; Katsuyama & McNeese, 1987; McNeese & Katsuyama, 1987). The machine learning mechanism will be proposed as a successive evolution of categorization programs. The initial implementation will be solely based on Quinlan's (1986) ID3 algorithm.

A basic question to address is why one would select machine learning programs as they might be unnecessary to model the processes referred to. The answer involves the nature of the phenomenon which is to be modeled. The data collected yield results of a very dynamical nature. Humans employ different strategies for recognizing faces as a function of the cognitive demands of a task as well as subsequent learning of familiarity of a given face. So, one of the reasons to employ machine learning is simply to see if simulated mechanisms of learning can model human learning. Therein, one can ascertain a goodness-of-fit between the algorithm and the actual learning observed in human subjects. Selection of classification programs and transitions toward conceptual clustering programs are specifically proposed as they tend to coincide with the theoretical explanations of what a human might be doing to recognize a pattern, (e.g., a face).

In particular, Quinlan (1986) points out that knowledge-based expert systems define learning as the acquisition of structured knowledge in the form of concepts, nets, or rules. Machine learning has come to be an important adage to these type of systems as it can be used to impart knowledge acquisition without expert intervention. The use of examples to induce decision trees by the ID3 program will be reviewed in the next section. It is in this context that the CEREBRAL WEEVIL model will grow.

Much of the results in the neuropsychology literature posit that a person comes to classify a face (in this case the face is seen as the "object") by different strategies which seem to be associated with either the left or right cerebral hemisphere. Thus, when a subject is presented a face to recognize, classification may occur by: 1.) piecemeal processes or 2.) configurational processes. Each of these processes are initiated by different conditions or attributes which are perceived by the person. Classifications based on piecemeal recognition occur usually in the right hemisphere and focus upon finding specific features for recognition (e.g., a nose); whereas, configurational classifications rely upon the person constructing a prototype schema (e.g., distances between the eyes, nose and mouth). There surely is a similarity between object classification learning in programs such as ID3 and object classification using the advantages inherent in each cerebral hemisphere.

The goal of this project is to emulate the cognitive processes that allow a person to perform most efficiently on a specific task. It is at this point that it might prove beneficial to think of the machine learning program as a replacement of the human in the experimental task. Although the task will have to be implemented within the constraints of the representation language and the elements of repetition within the tasks may have to be lessened, the program used should be emulative of the task itself. The inputs and outputs of task description will be provided in a later section, but first the idea of efficient performance by the human needs to be addressed more precisely.

One of the main dynamic components of efficiency on cognitive tasks is the amount of attentional resources a person has available for expenditure. If the resources are sufficiently low for single or dual tasks, then performance may suffer. Friedman & Polson (1981) propose that each cerebral hemisphere provides the human with separate, equivalent pools of

attentional resources, yet each pool is not accessible by the other. This is one of the first hypotheses to connect attention, hemispheric asymmetries, and performance into a coherent framework. Some of the theoretical predictions in hemispheric performance can be derived-in part- from this theory. Attention is mentioned only to introduce the attribute of resources which becomes important for a dynamic machine learning system to capture. Note too that the more evolved notions of machine learning programs may be more attuned to handle this greater complexity.

RELATED WORK

The basis for the machine learning model is ID3 (Quinlan, 1986) which is a nonincremental system that searches for patterns in examples after successive iterations of different training sets. This can be identified as a data-driven approach to learning by example. The BACON (Langley, Bradshaw, & Simon, 1983) and the INDUCE (Michalski, 1980) programs also use data-driven approaches to classification. These types of programs were selected as they share common mechanisms with the proposed human pattern recognition system as derived from the target experimental task and procedure (Katsuyama, McNeese, and Schertler, 1987). The ID3 program inducts a decision tree for classifying objects based upon particular values of attributes which identify these objects. The trees themselves are composed with these very attributes. CEREBRAL WEEVIL is initially formulated as a protracted version of the ID3 algorithm, hereafter referred to as ID3-CPO (Conceptually Pleasant Overextension). However, one of the major issues is the extent to which a nonincremental approach is advantageous.

Another type of approach would be the incremental conceptual clustering proposed in Fisher's COBWEB program (1987). This approach would tend to allow the model to be operational in real world and contextual environments that often increment observations which can effect the results of classification. This is in contrast to ID3 which is not responsive to order of acquisition. Dependent upon the circumstances specified for operation of the model, this may be useful. One may desire the incremental progression of classification but one may not want to be tied down by order of presentation. Yet, another advantage of the COBWEB work is the extent of prediction or inference of unseen object properties. Once again this would be an analogous mechanism similar to the experimental task in face recognition under ecological conditions of everyday encounters. The advantage may be specified as relating to the basic level in human classification systems. The basic level lies between the overly-general and the restrictive-specific classes which a human can access. Mervis & Rosch (1981) indicate that these basic kinds of classes are retrieved more quickly than these other classes and are hypothesized to be where inference-related abilities are maximized in humans. The question for this model is whether this is true for face recognition. A key point in COBWEB and basic kinds is the reliance on probabilistic representation of

attribute values. This supplies a representation that reflects incrementation and acts to place an object in a given class. In essence, probability replaces logical operators in a tree. This type of representation may yield an advantage for some of the attributes in the model.

An important point to make is that the ID3 algorithm may be more suitable to replicate data already summarized for an experimental study, whereas, the COBWEB algorithm would be more useful for a model in the real world perception of faces where probability of classification is fully developed and often times automatic. Note here that an observation is being made that the data taken from the experiment may not be generalizable to the real world itself. One of the key factors in this dilemma is this continuum of face recognition development which spans from the unfamiliar to the highly recognizable. This imparts major implications for the attention facet described previously.

One way to impart generalizability with specificity may be to create a model with both logical and probabilistic representations. This would be useful for summary as well as noisy context situations. Sclimmer's (1987) STAGGER system may provide the foundation for just such an approach. STAGGER allows concept acquisitions from conjunctive, disjunctive, and negated descriptions from noisy, discrete, and real-valued attribute representations. The system explores the useful idea of adapting representations to accommodate types of concepts to be classified. It is in this spirit that the CEREBRAL WEEVIL model is launched, although within the frugal confines of an ID3-CPO. The use of rules of engagement to change the way the system classifies objects via the ID3 algorithm is attempted. Rules of engagement are actually conditions associated with certain classifications. They are presented as means of adapting performance as a function of specific values of attributes which formulate a given classification. This is a kind of adaptive hemispheric learning procedure. Within the ID3-CPO version, these rules merely provide advice on how the system should change, whereas in a version that can readily access working memory, these rules would actually alter values in the state of the system.

One problem anticipated is the transition required between nonincremental and incremental absorption of examples. Theoretically, the system needs to assess states of hemispheric processing at strategic

criterion levels as well as individual example levels. The rationale here is that the individual examples are the dynamics which constantly feed into the formation of general strategies. Thereby, one look must be at the strategic level across all available examples (nonincremental) and another will need to access the example by itself (incremental). This paper only looks at the implementation of the strategic state, but in order to develop a complex representation the incremental state would also be necessary. An attempt will be made to remedy this by using rules of engagement that try to contextualize incrementation and probabilistic notions. In the concluding remarks section, discussion will again focus on integrating incremental with nonincremental methods.

As elaborated, another principle or mechanism which surfaced in the experimental data was the supplication of attentional resources with the consequent development of automatic processing. This is conceptually similar to the mechanism of "chunking" in the SOAR program (Laird, Rosenbloom, & Newell, 1986). Chunking is derived from the idea that performance improves via practice and that a series of subgoals performed initially may subsequently be replaced with learned chunks. Concomitantly, the amount of effort to process a chunk is substantially less than that to process each subgoal in sequence. Chunking nests well with two facets of hemispheric recognition. First, it relates directly to a person developing prototypes to use in recognition which seems to be based on a person's familiarity with an item. Second, the entire development cycle of "chunking faces" dynamically occurs through switching between the left and right cerebral hemisphere while exhausting various numbers of resources. Once, fluency completely develops for a face, the amount of processing resources used is significantly reduced. This is also mentioned in the cognitive attention literature (Shiffren & Schneider, 1977). Chunking may very well be fortuitous for a generalized system for scale-up; whereby, generalized recognition looms as the necessary and sufficient condition for successful performance. Other programs which create a mechanism such as SOAR may be tempting to use. Korf's (1985) use of macro-operators and Anderson's work (1986) with knowledge composition in ACT*STAR are supportive of this direction but they tend not to tie-in as well with the overall model as SOAR does.

THE DYNAMICS OF THE CEREBRAL WEEVIL SYSTEM

Because of the similarity of the experimental procedure and the machine learning program, it will be instructive to review the hemispheric face recognition task. Likewise, a review of the independent variables manipulated in the experiment provide a partial basis for determining the attribute-value parameters for the model. Finally, the results of the experiment provide the basis for hemispheric dynamics which will subsequently provide the rules of engagement for the model as well as the remainder of the attributes-value parameters. The goal of this part of the paper is to outline the task, inputs, outputs, and dynamics -in conjunction with- a high level description of the algorithm implemented.

CEREBRAL WEEVIL is implemented through the MacSMARTS™ (1987) knowledge system environment on a Macintosh Plus computer. The following discussion is highly aligned with the tools and faculties of this environment. For further information on using this environment to create the WEEVIL, please refer to the user manual described in Appendix A. Note that MacSMARTS™ embeds the ID3 algorithm within an expert system shell, wherein examples or rules may be used to compose knowledge bases.

A Database of Patterns with Specific Attributes

Within the actual experiments that predicated this work, subjects were presented 288 trials of faces for recognition patterns. The design consisted of the independent variables of Viewing Perspective (front, 3/4, or side view) crossed with Hemispheric Access (right or left cerebral hemisphere tachistoscopically presented stimuli) crossed with Trial Block Familiarity (1, 2, 3, 4); hence creating a 3 x 2 x 4 experimental design. Each trial block consisted of 3 x 2 possible conditions, wherein each condition was repeated 12 different times. Each trial block consisted of 6 x 12 or 72 total possible conditions. These are the experimental conditions that yielded the results which are to be modeled. For reasons of parsimony, 288 trials will not be used. The model will just initially use a universe of 35 example conditions.

The specific attributes used to impose characterization of a given face are as follows:

Internal Stimulus attributes

1.) Perspective of Transformation (P)

2.) Familiarization (F) (exposure frequency of a given face across trial block), and

External Stimulus context variables

3.) Attentional Resources (R) required to process face per hemisphere

4.) Hemisphere (H) to which a face is initially presented to.

Thus, for each face there are a total of 4 attributes. The model will begin with certain built-in resource capabilities but could be dynamically updated by the rules in conjunction with the type of face processed (assuming access to working memory is available). One of the interesting facets could be whether the categorization from ID3 can be used to subsequently reduce resources required to process the face. Table 1 shows how the combination of attribute-value pairs change across example faces.

Table 1

Attribute Values Per Object Face

		ATTRIBUTE VALUES		
Face	*(P -F -H)*	*Resources Expended per Task Demands*		
		SINGLE	DUAL	NO TRANSFER
1-3	F-1-L	LO	MED	MED-HI
4-6	NF-1-L	MED	MED-HI	HI
7-8	F-2-L	LO	MED	MED
9-10	NF-2-L	MED	HI	HI
11-12	F-3-L	LO	LO	MED
13-14	NF-3-L	MED-HI	HI	HI
15-16	F-4-L	LO	MED	MED
17-19	NF-4-L	MED	MED-HI	HI
20-21	F-1-R	LO	MED	MED
22-23	NF-1-R	MED-HI	HI	HI
24-25	F-2-R	LO	MED	MED
26-27	NF-2-R	LO	MED	MED
28-29	F-3-R	LO	MED	MED
30-31	NF-3-R	MED	MED-HI	MED-HI
32-33	F-4-R	LO	MED	MED
34-35	NF-4-R	MED-HI	HI	HI

THUS PARTIAL CROSSING OF RESOURCES WITH OTHER ATTRIBUTE VALUES YIELDS A TOTAL OF 35 EXAMPLE FACES FOR 1 REPITITION.

P= Perspective, F= Familiarity, H= Hemisphere accessed,

NF= Non-frontal, F= Frontal,
1= Unfamiliarity, 2= Low familiarity, 3= Medium familiarity, 4= High familiarity
L= Left hemisphere, R= Right hemisphere

Note that we have just used the nominal values of low, medium, medium-high, and high for specifying attentional resource levels in a given example (and the engagement rules) and that we have reduced perspective down into two values (i.e., frontal versus nonfrontal faces). The resource values are representative of single and dual task conditions (face recognition plus semantic recognition simultaneously processed). Note however, that every value of the resource attribute will not be fully crossed with the other 3 attributes. This is due to the fact that the same resource expenditure may occur with different attribute valuations. The prescription of resources that each face exhausts from a hemispheric pool was taken from actual subject difficulties encountered with each face in conjunction with other data about hemispheric processing.

One of the dynamics of processing is for a comparison to be made between the current levels of resources specified in the hemisphere accessed and the amount of resources that the current task composition is depleted by. This may be accomplished by defining an initial level of resources and incrementing that level as a function of the unique order of faces presented to it. This makes the dynamic dependent upon order but this is true in everyday activities. If a category becomes automatized, then prior to depletion, a disengagement would occur as *fluent processing does* not require attention. Note too that the incrementation would subtract the specified amount of resource from a constant increase in hemispheric resource each time an example single or dual task is processed. This simulates the notion of resources rebounding from exhaustion. If there is not a recovery of attentional strength, then there would never be enough resources to accomplish tasks in either hemisphere. What is crucial is the threshold level in which hemispheric transfer is necessary to continue. Such dynamicism is not possible in ID3-CPO, yet it is proposed for modules that connect classification as operatives that-in conjunction with rules of engagement- perturbate actual quantitative and qualitative performance levels. These more complex notions would rely upon feedforward and feedback mechanisms as well.

Rules of Engagement

The objects (faces) will be subjected to problem solving rules of engagement which suggest what action the accessed hemisphere must take. This action has the implication of performance levels for single and dual

task conditions, and the amount of resources expended. Each time a face is presented to the rules, certain levels of problem solving ensue with certain performance results and certain resource depletions. After each training set pass, ID3 categorizes these faces based on certain attributes which are learned. The MacSMARTS™ environment allows these rules to be associated directly with the attribute-values of every example face. Therein, the program learns how to apply rules to certain classes of examples, dependent on the induction of decision trees used for a given training set. Appendix B. provides examples of such rules.

AN EVALUATION OF CEREBRAL WEEVIL

The demonstration of the algorithm for CEREBRAL WEEVIL may be viewed as a systematic progression of stages, each of which is evaluated as separate modules. In this way, comparisons can be made with ongoing and past experiments to gain maximum utility from the model. With each stage, it is anticipated that a more substantial algorithm and more highly evolved representational language may be necessary. Hence, each modular addition to the overall model can be tested to ascertain whether any advantages accrue, and whether there is a tradeoff with other components and performance of the model. The intent of this evaluation is to observe the performance of the ID3-CPO component for classifying faces.

Once the ID3-CPO module was implemented, an empirical test was conducted to demonstrate performance results in terms of the learning set. Specifically, the independent variable for this experiment was the extent of training objects obtained from a universal sample of all possible objects. This may be operationally defined as the percentage of training objects used as a sample. There were four levels of the independent variable: 25% test set, 50% test set, 75% test set, and 100% test set (which represented the universe). The dependent variable used to assess performance was accuracy. The percentage of correct rules of engagement (provided in association with classification parameters) for each level of the independent variable represents accuracy in this experiment. Other measures such as cost were not assessed at this point due to relative ease of implementing this module and the negligible drain on memory given the sample size of each set tested (e.g. 9, 18, 26, and 36 objects, respectfully). However, cost will be a consideration as more modules are implemented.

Figure 1 graphically provides results of the experiment. As shown, the relative success of inferring engagement rules does not occur until the 75% test set and this is just slightly over 50% correct. Hence, the system does not begin to have high reliability of inferencing until the 85-90% range. In part, these results demonstrate the need for further development in the areas of incrementation and probabilistic knowledge representation to address noise in the samples. The construction of additional modules is hypothesized to produce more directed inferencing such that high reliability would begin in the 50-60% range. This first test provides a watermark upon which to judge successive implementations.

One reason the inference ability does not appear until the 85-90% range may be due to high interdependency that is established by the resource allocation factor as it is not completely crossed with the other factors.

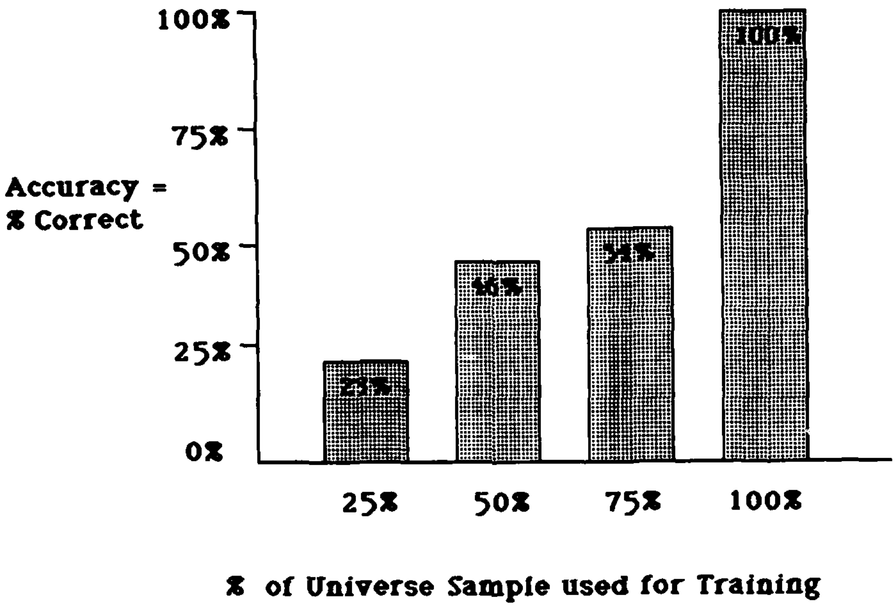

Figure 1. Inference performance over % training set

Langley (1987) suggests that another way to evaluate the system is to compare it with human learning. In many ways human learning is the raison dêtre of CEREBRAL WEEVIL. Indeed, the formulation of the engagement rules, the objects, and the attribute-value pairs were either directly taken or derived from experimental results in hemispheric processing. In fact the attributes of familiarity and resource availability directly tract with the perceptual learning of faces. In the ID3-CPO module, an attempt has been made to simulate human learning of faces as the faces become more familiar. However, the learning is perturbated by the complex problem of allocating resources as "sustenance" to continue to propel the learning. Because ID3-CPO- as currently implemented- does not draw on values in working memory, these two human learning aspects must be simulated. This reveals an interesting facet of machine learning programs.

On the one hand, inference ability is desired as a efficacious and smooth transitional process for performance-based systems. This can be contrasted with human learning systems (as exemplified by empirical approaches) which often show signs of messiness, bias, and "climax learning". In many circumstances the performance shown in Figure 1 is similar to the actual trial-to-trial performance of subjects. The learning strategies which subjects employ tend to be either: a.) immediate recognition, or 2.) prototype formation which requires many examples before climax recognition occurs. The performance of the ID3-CPO module is very much representative of prototype strategy formation. It also demonstrates the nonincremental nature that results after many extractions. In conclusion, the evaluation suggests that CEREBRAL WEEVIL has partially modeled human performance in a pattern recognition task. Yet there is room for improvement, both on empirical and performance levels. The following section briefly reaffirms the commitment to develop additional modules to address these problems.

CONCLUDING REMARKS

One of the hazards of using the ID3 framework is the necessity for a voluminous amount of training examples to approach correct generalizations. As Porter & Kibler (1986) aptly state the volume of training examples does not always provide correct generalizations. Training may even be described as fortuitous. Stated in terms appropriate to hemispheric processing, this suggests that if a face is representative of the currently constructed prototype then the face has a high probability of recognition. However, if the face deviates from the prototype, whereby, a new prototype or another strategy may be required, then this instantiation acts to discard the the current best strategy. However, the brain adjusts very flexibly to assimilate the face via another method. CEREBRAL WEEVIL currently can emulate human learning on the first step. What remains is to evolve the system to regulate it's performance. Such regulation requires at least two new elements and probably more. First, the WEEVIL must have other learning powers upon which it can bias itself. Here, bias is used in the sense that the system biases itself towards another learning power upon experiencing dead-ends in the current power. This is similar to notions expressed by Utgoff (1986). This means building up extensions of the ID3-CPO or new interactive modules that procure new representational and procedural biases. Specifically, the areas of incremental clustering, probabilistic representation, and incremental adjustment are all good candidates for future work. The point to be remembered is that the system must remain integrated to form a machine learning collage that regulates the method according to the performance sampled.

One proposal for such a system would connect nonincremental and incremental methods together to transition between either strategy, based upon the appropriate cognitive strategy. These two algorithms may proceed in parallel, but the key is that they are mutually deterministic. An integration may proceed by creating a version-like search space (see Mitchell, 1982) of possibilities between incremental and nonincremental solutions. The convergence on the proper state could be based on an evaluation metric that compares the extent of divergence for each incrementation with the current best generalized, strategy tree. This metric could be averaged for each case such that initially a "best fit" could occur at a state half way between the incremental and nonincremental classification. With successive training sets, one would observe how the

system learns to learn by using a version search strategy to learn which is the best learning algorithm to use. This would be important as well for the cognitive model as it would represent how the brain adapts from one strategy to another as a function of developing familiarity with attributes. In fact, interesting tradeoffs could be observed between incremental, developmental, and automatic strategies in learning faces to be recognized. Once the system settled down, a specific probabilistic representation could be designated for preference between strategies of a given training set. The generalized nonincremental strategy could be changed by a teacher or the system itself could act as the teacher in a way akin to the SAGE system (Langley,1985). Hence, a statistical equilibrium between machine learning strategies becomes contingent on learning search heuristics. Inherently, the incrementation-nonincrementation continuum always reflects the current learning of the organism. Certainly, this is analogous to the human learning by adaptively using both sides of his/her brain.

The second need revolves around creating and accessing working memory knowledge that can portray variables as continuous, discrete, nominal, or numeric-probabilistic states. By directly linking the modules through a common working memory, traces can be used to direct search, and values can be immediately percolated through the system. Consequently, the system can be self-regulative across many variations. This allows a greater dynamicism and also allows greater flexibility in creating rules of engagement. The ability to draw on knowledge in working memory allows sensitivity to knowledge that spawns greater generalizations and thus creates a much more robust system. Psychologically, it also allows development of cognitive models for determination of when and how inert knowledge occurs.

In conclusion, it has been the author's hope to develop a machine learning model of hemispheric cognition, within the context of discovering issues related to implementing learning mechanisms as well as understanding psychological reality. The approach taken might be classified as "empiricity". Learning mechanisms are modeled based on an empirical analysis of psychological reality and are subsequently tested empirically for their demonstration of that reality. Any variation in differences are considered in terms of changes to both future experimental studies of humans, and new evolvements in the programs used to model the reality. This approach has been successful in this first model as it

provides an evolutionary path of hemispheric cognition that signals where the psychological research and the machine learning model have been, where they currently stand, and where they must go; as well as forecasting the means to get there. Finally, this project has truly demonstrated the necessary interdependence between mechanisms of human and machine learning that can act to espouse the epicenter for future cognitive science efforts.

APPENDIX A

A User's Guide into CEREBRAL WEEVIL

User as Cognitive Psychologist

First, this guide will seek to introduce an understanding of how to use CEREBRAL WEEVIL. Much of the information for this appendix will be drawn from the MacSMARTS™ user manual (1987), but placed in the context of using and creating the WEEVIL. Before describing how a user works with the system, it is desirable to paint the landscape upon which the user is juxtapositioned.

The user in this context is the cognitive psychologist. The user desires to present the homunculus (WEEVIL) with different possibilities or combinations of the independent variables to see how the system classifies these examples. The system may respond in a way that indicates a certain level of performance and/or suggest how adaptation for better performance can occur (e.g, suspend operations in current hemisphere and switch to opposite hemisphere for more efficient performance). Therein, when a user assumes the role of psychologist, he/she is basically running an experiment to see how WEEVIL responds to the example selected. The variability supplied to such experiments may occur by manipulating the independent variables, the dependent variables, the size of the training set, and other conditions allowed by MacSMARTS™. The WEEVIL actually has two modes of operation. The mode used when the user assumes the role of psychologist is termed "rat race". It implies that the user accepts the default values currently programmed into the system and proceeds by running the system in a hypothesized experiment. If the user wants to go beyond what the current system knows, he/she assumes the role of knowledge engineer and enters the mode termed "surgeon". This mode allows the user to perform surgery upon the homunculus to create a new art of the state. The role of the user as knowledge engineer will now be described.

User as Knowledge Engineer

The user may assume this role upon sensing that the system does not capture necessary conditions to be tested in the experimental run. The

underlying function of WEEVIL is to test out predictions based on the learning derived through certain training sets and different attribute-value pairings. Hence, if one wants to prescribe changes that go beyond current valuations, then there must be a switch into the surgery mode. In order to do surgery, some basic tools of the operating environment must be introduced. The tools that the user has available are a mouse, a user interface consisting of a variety of windows, menus, buttons, and spreadsheets for entering examples. For more specific information refer to the MacSMARTS™ manual. At this point, it would be useful to take a guided tour of the operating room and define the underlying form of the WEEVIL upon which the tools of surgery must be applied.

The first stop is the knowledge base. It forms the brain of the system. To access the knowledge base a user must pull down an operating menu entitled, "example editor". The menu is accessed from a title at the top of the screen termed "logic". There are three main components of the example editor. They are factors, advice, and examples. One must select factors to encode new independent variables. The user moves the mouse to the "new" button and then types in the new variable(s) desired. If variables are to be removed the user just moves the mouse to highlight the variable to be removed, then moves the cursor to the cancel button. After, a new variable is programmed, it will appear in the "factor window" on the left side of the screen. On the right side of the screen the user must type in the various conditions associated with the independent variable. They are termed "choices" and are entered the same way as factors. Once entered they appear in a "choices window" on the right side of the screen.

Note that at the top of the screen the user may supply complete questions associated with each factor entered. This allows the system to prompt the user with a question to supply the necessary parameters when in the ratrace mode. The next step is for the user to enter classes of advice (rules of engagement) for the system. A user may cancel advice as well. This is accomplished by the same mousing operations explained for creating/cancelling factors. Once again statements to elaborate the advice may be typed in at the top of the screen. Once this step is completed, the user progresses to example creation. A user highlights the new button to create a new example or highlights the cancel button (once the cursor has been moved to the example number which is now shown in the example spreadsheet) to remove the example. The spreadsheet columns show the

example number, the factors currently programmed in the system, and the associated advice. The user must supply the respective parameters for each factor and advice attached to each example. This is the information typed into the rows of the spreadsheet. Once a set of examples are complete, then the user clicks on "done".

The next stop in the tour completes the surgery. It is now time to envoke the ID3 component. To do this the the user clicks on the logic title and pulls down the menu whereupon the selection entitled "create example based rule" is highlighted. This lets ID3 operate on the training set currently used. It responds with a logic worksheet that shows the general relations between facts, rules, and advice. At this point the WEEVIL is in the recovery room having just undergone surgery. If the user desires to run the system, he /she must go to the logic title and pull down the menu and select "run advisor". This move now returns WEEVIL to the ratrace mode, whereupon it asks the successive questions associated with the new parameters programmed into the system. To try different example faces, the user merely clicks on the "rerun" button and the system clears itself to run the next example. If another previously created (and saved) test set is desired, the user clicks on the "get new KB" button and the system shows all the KBs available. The user highlights the one required and continues as previously described.

This then concludes the user's guided tour of the operating environment. Although brief, it encapsulizes the basics of the system. If additional information is desired please contact the author or consult the MacSMARTS™ users manual.

APPENDIX B.

Examples of Rules of Engagement

```
MacSMARTS.log

Date:Tuesday, November 28, 1989Time:11:49 AM
Reply:      FRONTAL VIEW
Question:   What hemisphere is the face presented to?
Reply:      RIGHT HEMISPHERE
Question:   What level of familiarity does the face possess?
Reply:      LOW FAMILIARITY
Question:   What is the level of resources expended?
Reply:      LOW
Advice:     HEMISPHERIC CONTROL:Do not transfer control to the other hemisphere; continue to process in hemisph

Rerun
Question:   What is the perspective of the face presented?
Reply:      NONFRONTAL VIEW
Question:   What hemisphere is the face presented to?
Reply:      LEFT HEMISPHERE
Question:   What level of familiarity does the face possess?
Reply:      UNFAMILIAR
Question:   What is the level of resources expended?
Reply:      MED-HIGH
Advice:     HEMISPHERIC CONTROL:The system has adapted to produce efficient perf on the ling task but less than

Rerun
Question:   What is the perspective of the face presented?
Reply:      NONFRONTAL VIEW
Question:   What hemisphere is the face presented to?
Reply:      RIGHT HEMISPHERE
Question:   What level of familiarity does the face possess?
Reply:      UNFAMILIAR
Question:   What is the level of resources expended?
Reply:      HIGH
Advice:     HEMISPHERIC CONTROL:The system has adapted to produce efficient perf on the face task but less than


Question:   What is the perspective of the face presented?
Reply:      FRONTAL VIEW
Question:   What hemisphere is the face presented to?
Reply:      RIGHT HEMISPHERE
Question:   What level of familiarity does the face possess?
Reply:      HIGH FAMILIARITY
Question:   What is the level of resources expended?
Reply:      LOW
Advice:     HEMISPHERIC CONTROL:Do not transfer control to the other hemisphere; continue to process in hemisph

Rerun
Question:   What is the perspective of the face presented?
Reply:      NONFRONTAL VIEW
Question:   What hemisphere is the face presented to?
Reply:      LEFT HEMISPHERE
Question:   What level of familiarity does the face possess?
Reply:      HIGH FAMILIARITY
Question:   What is the level of resources expended?
Reply:      HIGH
Advice:     HEMISPHERIC CONTROL:The system has adapted to produce poor performance on all tasks demanded.

Question:   What is the perspective of the face presented?
Reply:      NONFRONTAL VIEW
Question:   What hemisphere is the face presented to?
Reply:      LEFT HEMISPHERE
Question:   What level of familiarity does the face possess?
Reply:      LOW FAMILIARITY
Question:   What is the level of resources expended?
Reply:      MEDIUM
Advice:     HEMISPHERIC CONTROL:Try to transfer from current hemisphere to other; else suspend operation and

Rerun
Question:   What is the perspective of the face presented?
Reply:      NONFRONTAL VIEW
Question:   What hemisphere is the face presented to?
Reply:      RIGHT HEMISPHERE
Question:   What level of familiarity does the face possess?
Reply:      HIGH FAMILIARITY
Question:   What is the level of resources expended?
Reply:      MED-HIGH
Advice:     HEMISPHERIC CONTROL:The system has adapted to produce efficient perf on the face task but less than
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